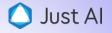


## On the way to industrial NLP-platform:

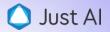
transformers, microservices, architecture



#### Contents

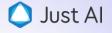


- New classifier for our chatbot platform
- Paraphrase for user inspiration
- Problems with old NLP service
- The new ML platform



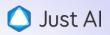
## Models for products

## Classification is everything



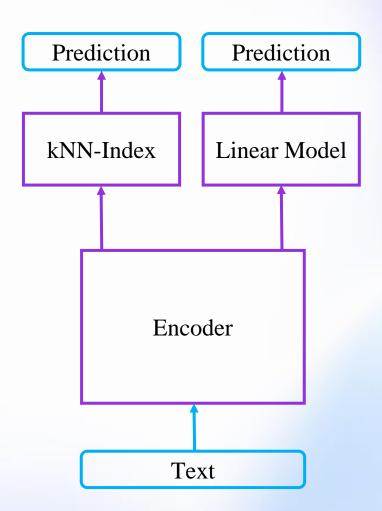
- There are many difficulties and they are known:
  - Closely related classes
  - Imbalanced classes
  - Too few samples
- Problems are solvable for DS
- And are NOT solvable for our regular users
- Classifiers should always work well out of the box

## Transformer for platform

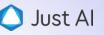


Transfer Learning is a good all-round solution for complex cases

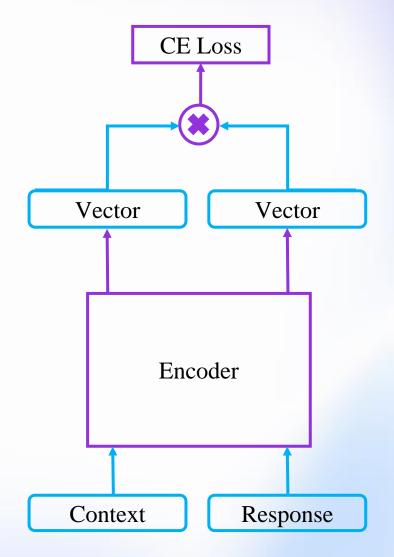
- Use pre-trained BERT-like models with better understanding of the meaning of the text
- Add lightweight trainable head
- Get a good classifier working out of the box



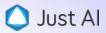
### Fine-tuning



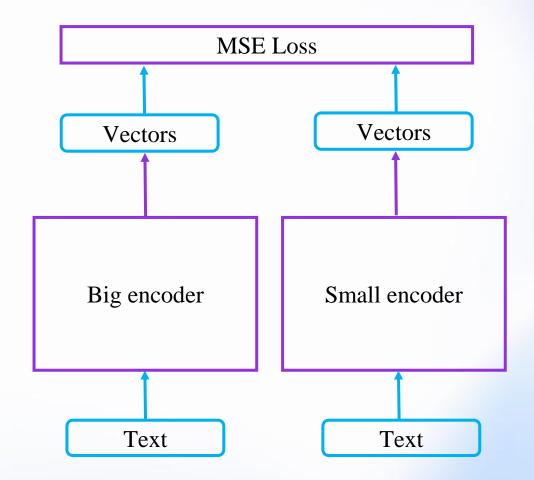
- Internal dialog dataset (> 1M dialogs)
- Proxy task: increase similarity between a phrase and its context
- Result: +5% on average to the accuracy of the best model with a linear head



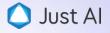
#### Acceleration



- Distillation + ONNX:
  - CPU speedup: x4.5
  - GPU speedup: x1.7
  - Average accuracy loss: < 1%</li>



#### Benchmarks



• 10 datasets in Russian from different chatbots subject areas

- Typical dataset example:
  - 50 classes
  - 430 train samples
  - 290 test samples

- 3 / 10 datasets are public:
  - HWU-20 Ru \*
  - Chatbots-Ru \*
  - Russian Intents Dataset \*\*

<sup>\*</sup> https://github.com/AutoFAQ/Intent-Recognition-SaaS-Evaluation

<sup>\*\*</sup> https://www.kaggle.com/datasets/constantinwerner/qa-intents-dataset-university-domain

#### Results



- What is being compared:
  - New Transformer classifier (inside our platform)
  - Updated old Classic ML (log-regression) and DL (CNN) algorithms (inside our platform)
  - Dialogflow classifier (inside its platform)

#### Average results for 10 datasets:

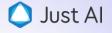
Classifier	F1-micro	F1-macro	
Classic ML	0.768	0.704	
DL	0.794	0.741	
Transformer	0.841	0.803	
Dlalogflow	0.785	0.745	

## Results for public datasets



Dataset	Classifier	F1-micro	F1-macro
HWU-20 Ru  Classes: 20 Train: 100 Test: 100	Classic ML	0.67	0.65
	DL	0.80	0.79
	Transformer	0.92	0.92
	Dlalogflow	0.72	0.72
Chatbots-Ru  Classes: 79 Train: 5.6K Test: 1.4K	Classic ML	0.73	0.71
	DL	0.78	0.77
	Transformer	0.85	0.83
	Dlalogflow	0.63	0.62
RID  Classes: 142 Train: 13K Test: 900	Classic ML	0.95	0.94
	DL	0.93	0.93
	Transformer	0.95	0.95
	Dlalogflow	0.94	0.94

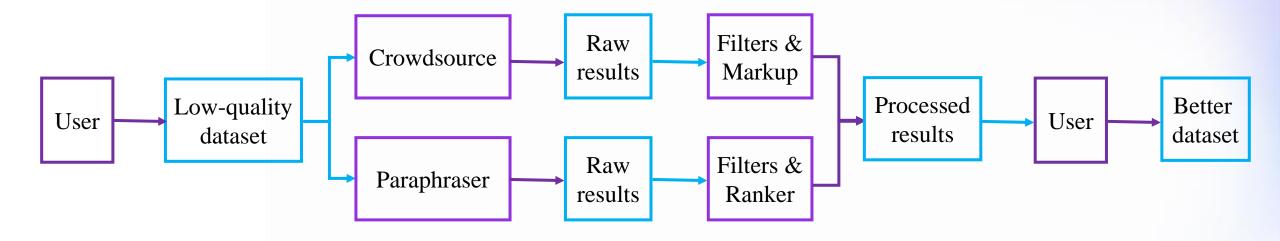
#### Additional help for the user



- It happens that there are no training data and logs to create them
- Sometimes users try to compose train phrases, it is a slow process
- The resulting samples have problems:
  - small dataset size
  - poor vocabulary
- Dataset expansion and inspiration options:
  - Crowdsourcing
  - Paraphrasing

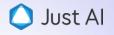
#### Product scenarios





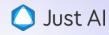
	Crowdsourcing	Paraphrasing
Dataset size	~10²	1
Duration	Tens of minutes	Seconds
Price	High	Low
Quality and diversity	Good	Customizable
Tasks complexity	Higher	Lower
Solution	Toloka (RU)	T5-based model

#### Paraphrase model

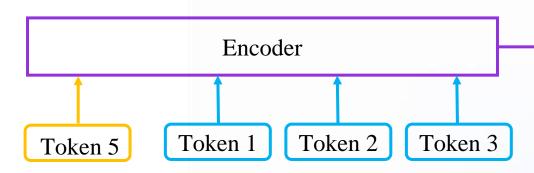


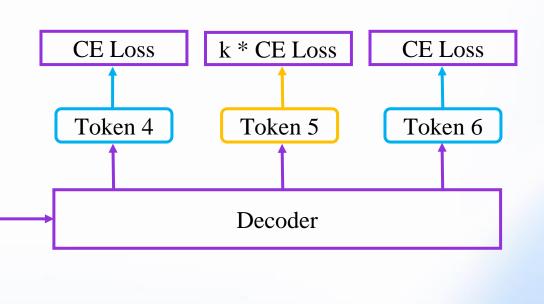
- Sequence-to-sequense task
  - sberbank-ai/ruT5-base (Russian)
  - t5-base (others)
- Open datasets + backtranslation of open and company internal data
  - > 2M phrase pairs (per language)
- Encourage specific substrings to appear in the result (to use with NER)
  - Special attention to dates
- Different generation parameters presets

### Training with text generation control



- Commutative samples
- Hint model with a prompt-segment
- Multiply the penalty for sequences from the prompt-segment
- Apply to  $\frac{1}{2}$  random samples, k ~ 10





## Examples



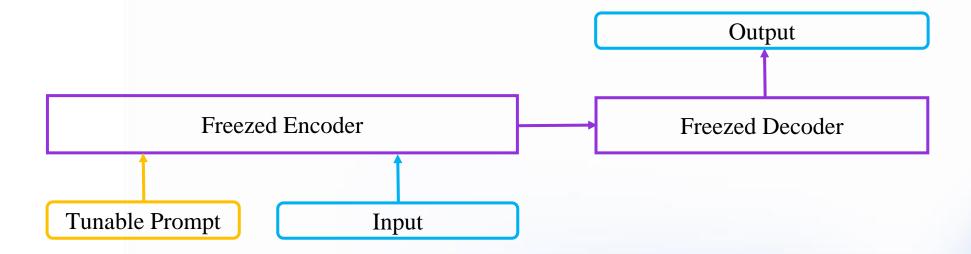
Original phrase	Add	Remove *	New phrase
За окном снег, а значит скоро новый год, ура!	-	-	За окошком снег и, следовательно, скоро Новый Год! Ура!
Санкт-Петербург назван в честь святого Петра	-	-	Петербург носит имя Святого Петра.
Хочу закрыть счет в вашем банке	аккаунт	хочу	Я хотел бы закрыть свой аккаунт у вас в банке.
Курьер сообщил, что у него нет части заказа, я хочу вернуть деньги.	монеты	-	Курьер сказал, что части заказов у него не было, мне монеты хочется вернуть.
Курьер сообщил, что у него нет части заказа, я хочу вернуть деньги.	новый год	заказ, заказа	Курьер в новый год сказал, что не имеет части ордера, хочу возврата.

<sup>\*</sup> removing is implemented through bad\_word\_ids in transformers

### Add style options via prompt-tuning



- New model capabilities without retraining
- Example: text simplification
- RuSimpleSentEval dataset \*
- Trained model Prompt-tuning (ru-prompts library \*\*)



<sup>\*</sup> https://github.com/dialogue-evaluation/RuSimpleSentEval

<sup>\*\*</sup> https://github.com/ai-forever/ru-prompts

## Examples



#### **Original phrase**

#### **New phrase with simplification**

Пётр I Алексеевич, прозванный Великим (9 июня 1672 года — 8 февраля 1725 года) — последний царь всея Руси (с 1682 года) и первый Император Всероссийский (с 1721 года).

Пётр I Алексевич был последним царем Руси с 1682 и первым Императором Всея Руси с 1721

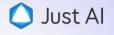
Пушкин один из самых авторитетных литературных деятелей первой трети XIX века.

Пушкин - авторитетный литературный деятель первой трети 19 века.

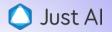
В природном очаге заражение обычно происходит через укус блохи, ранее питавшейся на больном грызуне.

Заражение происходит из-за укуса блохи.

#### **Evaluating models**

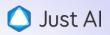


- Several assessors evaluate on general and subject phrases
- Correctness score (200 samples) 70% for the best model:
  - Meaning preservation
  - Grammar and incorrect words
  - Diversity
- Required words appearance score (170 samples) 80% for best model
- Average simplification length reduction (75 samples) 25%

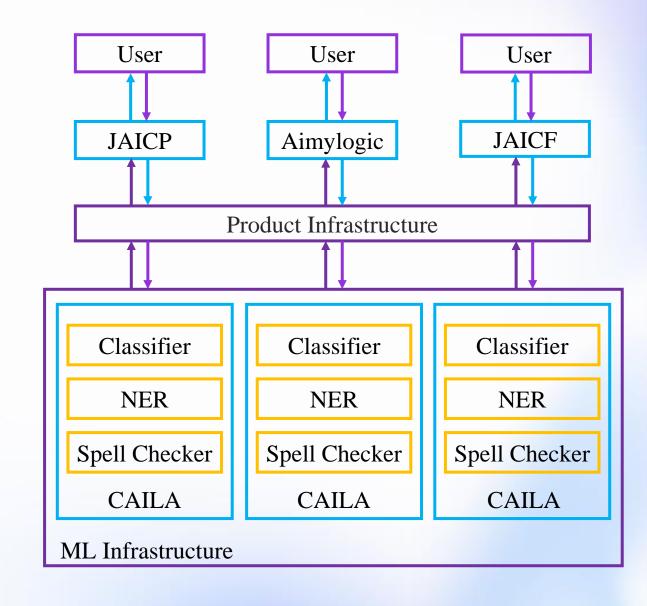


## Platform for models

## Where to integrate new models



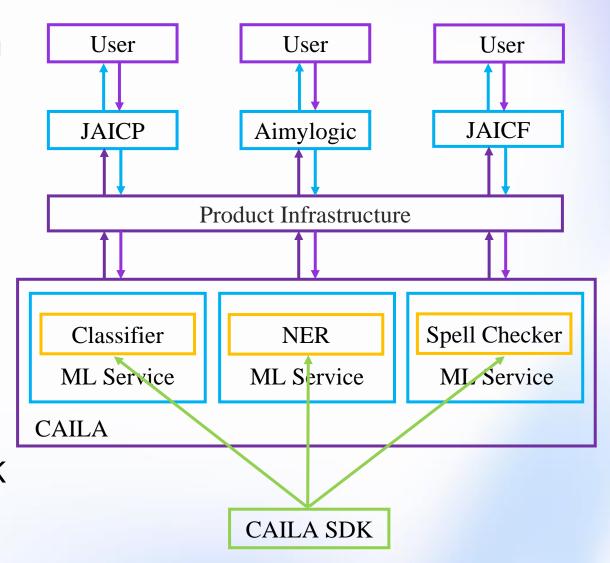
- Conversational Al Linguistic Assistant (CAILA) — internal NLP provider for company products
- Monolith service containing variety of solutions
  - Wasteful resource consumption
  - Hard to scale
  - Troubles with integrating new solutions both in NLP service and in products



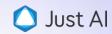
## CAILA 2.0: from service to platform

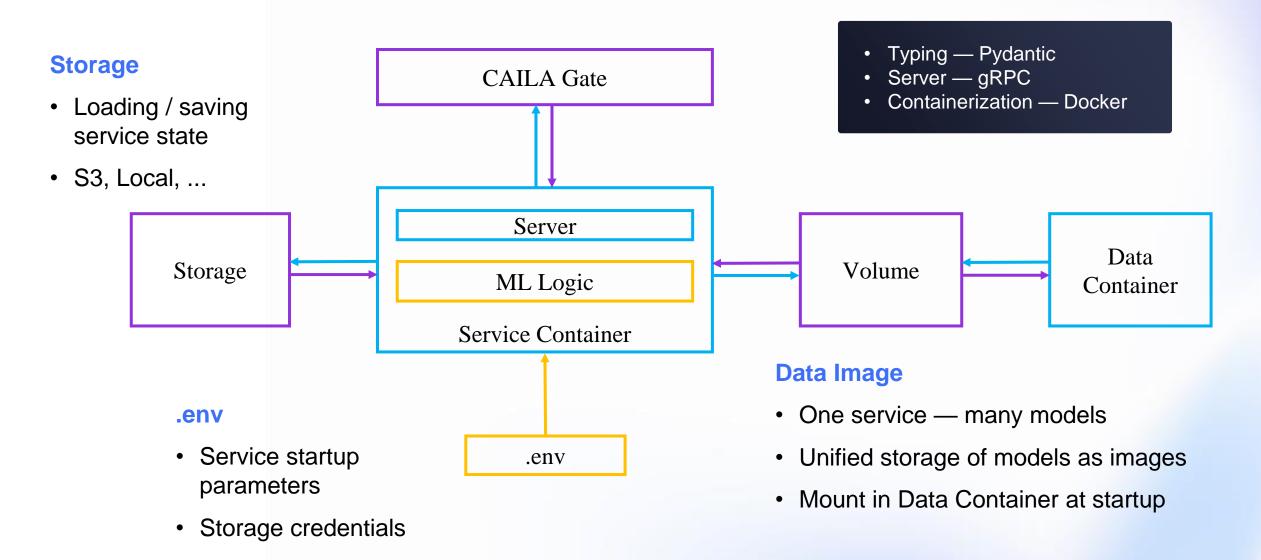


- Now CAILA is a platform for creating, hosting and managing ML services
- One NLP tool one microservice
- One public SDK for all services
  - interfaces, base classes and mixins
  - input and output data types, type checking
  - interactions with CAILA, storages, loggers
- Service languages are Python and Java
- User models can be added to CAILA via SDK
- Integration with projects in Just AI tools



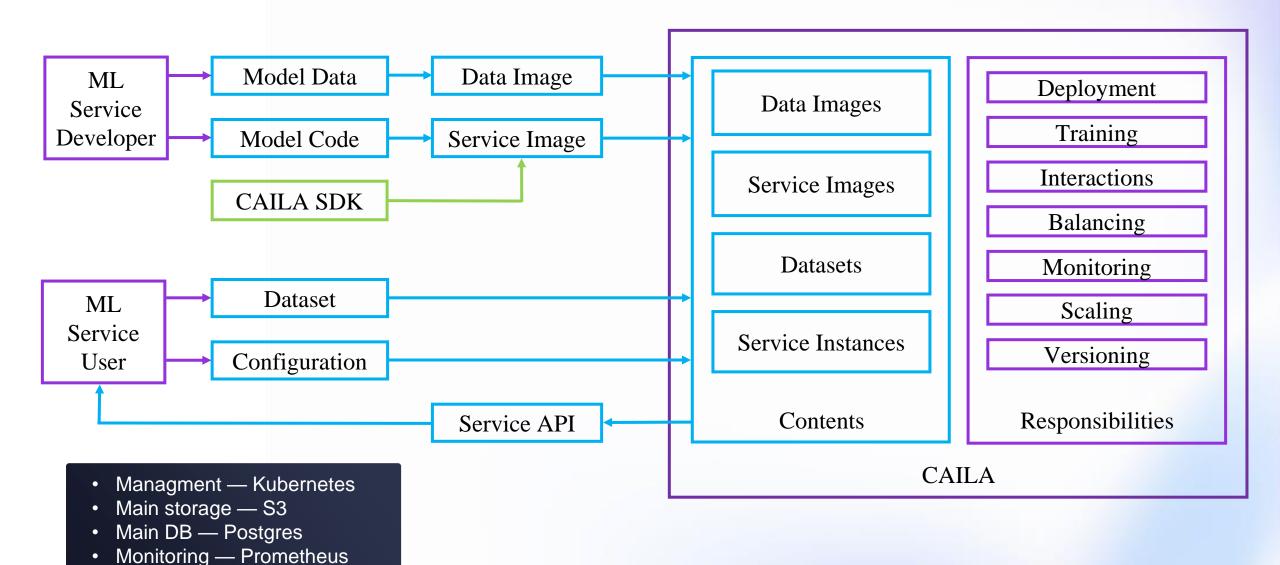
## General microservice diagram





## Platform overview diagram

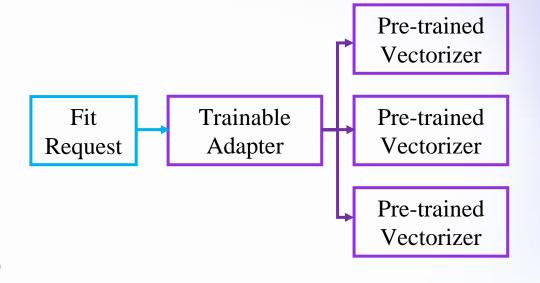


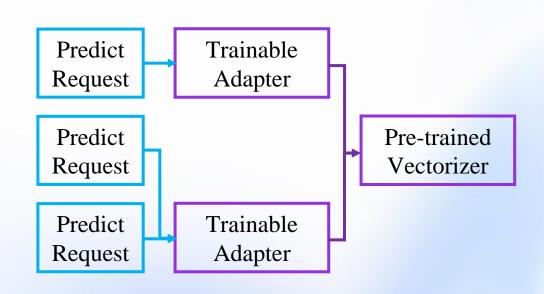


#### New classifier in CAILA 2.0

Just Al

- Services can communicate with each other through CAILA Gate
- Classifier = vectorizer + adapter services
- Adapter can be ML or KNN (we use NMSLIB)
- Parallelization of heavy fit requests across vectorizers
- Dynamic batching of predict requests
- Vectors caching in storage during training





#### How do we use the new platform



#### Build our ML services

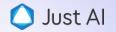
- We transfer all our NLP services to CAILA
- Integration of Just Al voice technologies is next

#### Use as ML provider for our products

- Just Al Conversational Cloud products are switching to work with CAILA services
- The new Transformer calssifier is available in JAICP (upon request for now)

#### Open CAILA to external users

- Cloud platform with monetization for ML developers and customers
- On-premise installations for corporate clients

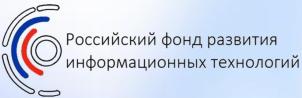


# Thank you for your attention!



app.caila.io







TG: @MelLain